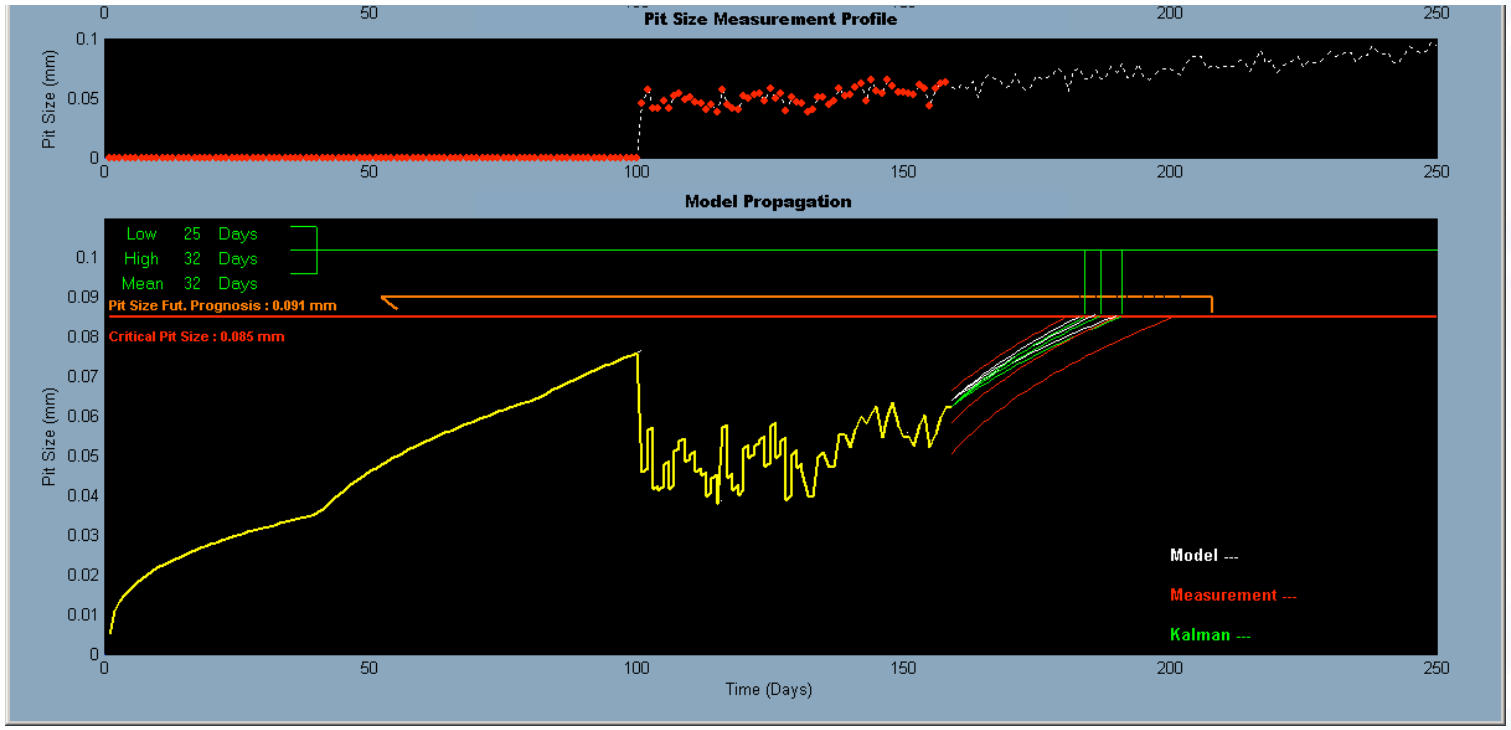
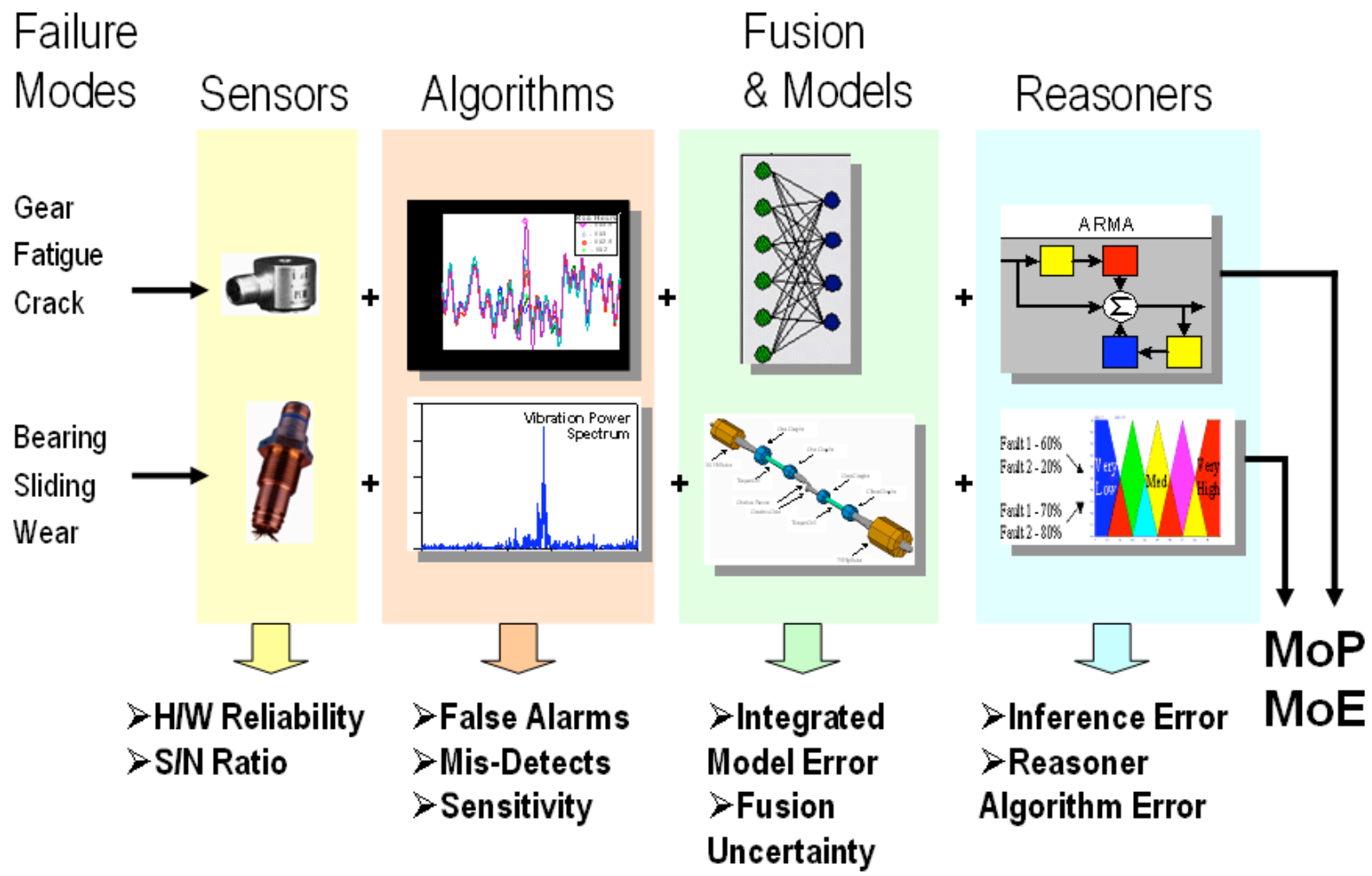
An Overview of Selected Prognosis Technologies with Reference to an Integrated PHM Architecture

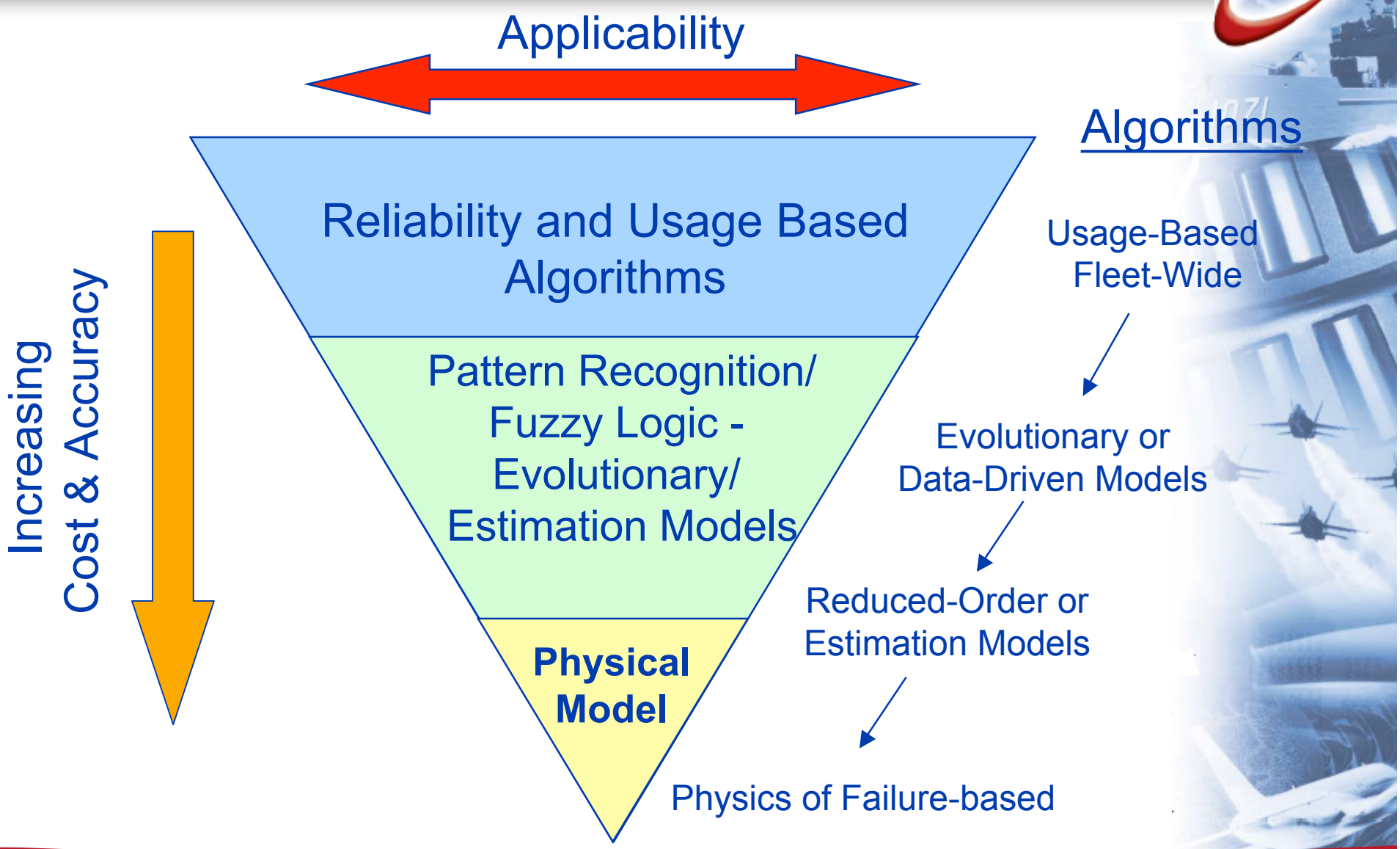


Roemer, M.J., Byington, C.S., Kacprzynski, G.J. and Vachtsevanos, G.

Prognosis Technologies at ALL Levels



Prognosis Technical Approaches



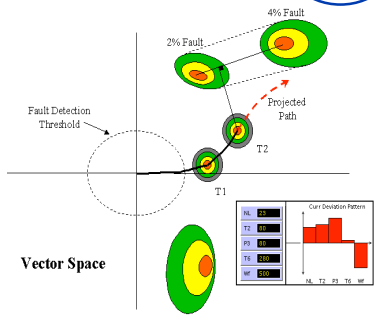
Application of Prognosis Approaches

PHM Priority Areas

1. System Components
   - •Gears/Bearings
   - •Shafts/Couplings
2. Performance
   - •Degradation
   - •Wear
3. Drive Train
   - •Vibration
   - •Oil Analysis
4. Actuation
   - •Hydraulic
   - •Electrical

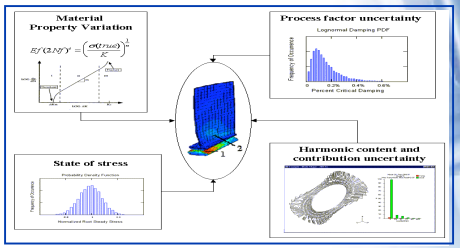
Approach & Algorithms

Performance Evaluation

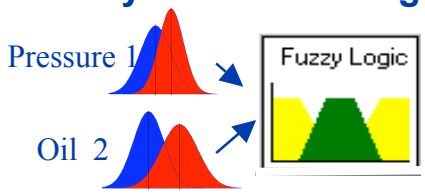


Component Degradation

- •Physics-based
- •Real-time life prediction

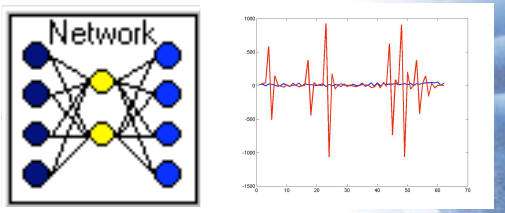


Gray-Scale Trending

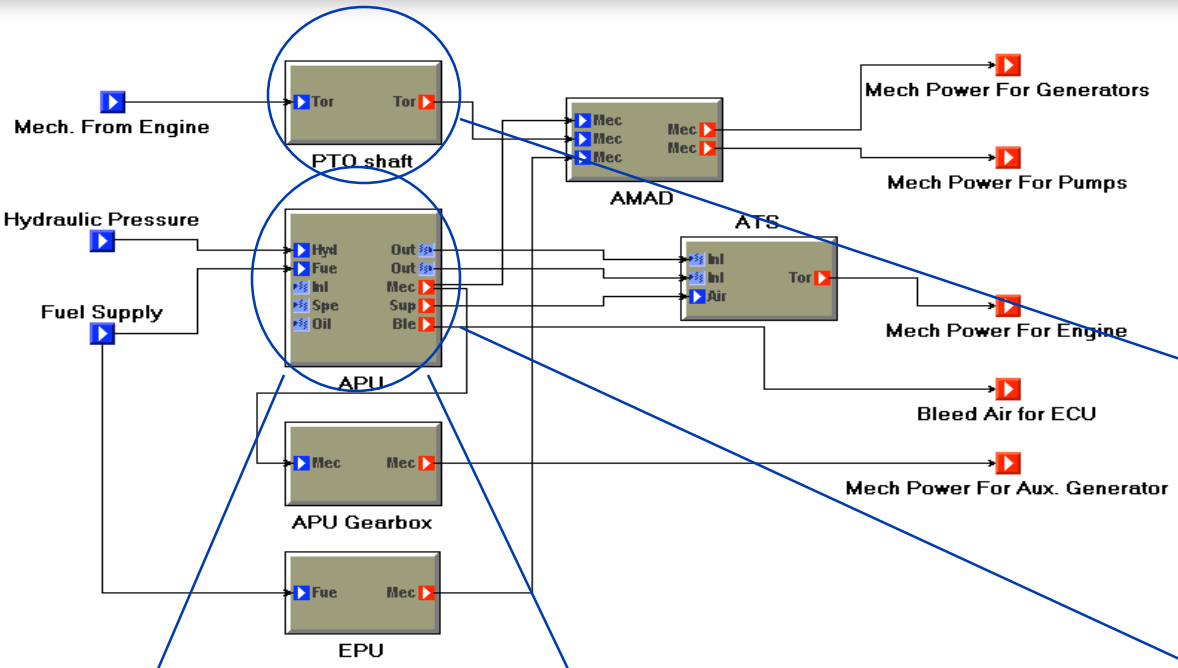


Signal Analysis

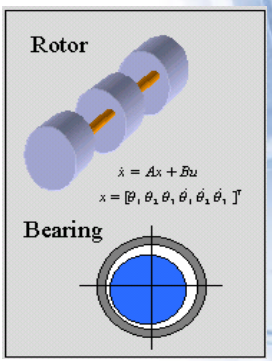
- • Anomaly Detection
- • Sensor Fault Isolation
- • Feature Prediction



Prognosis Integration Across Vehicle

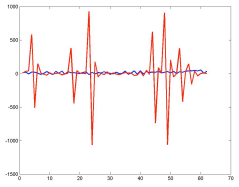


PTO/AMAD Health



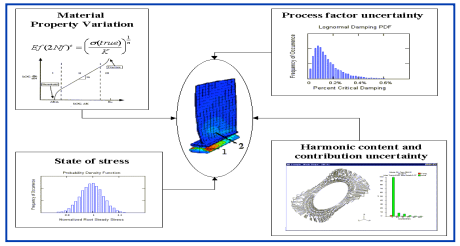
Valve Diagnostic Health

- Anomaly Detection
- Sensor Fault Isolation
- Virtual Sensing

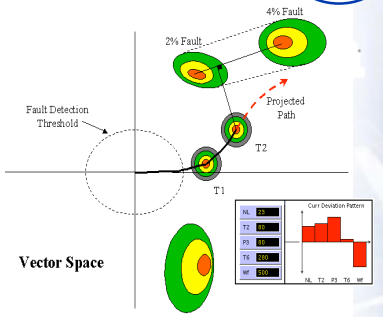


Turbine Degradation

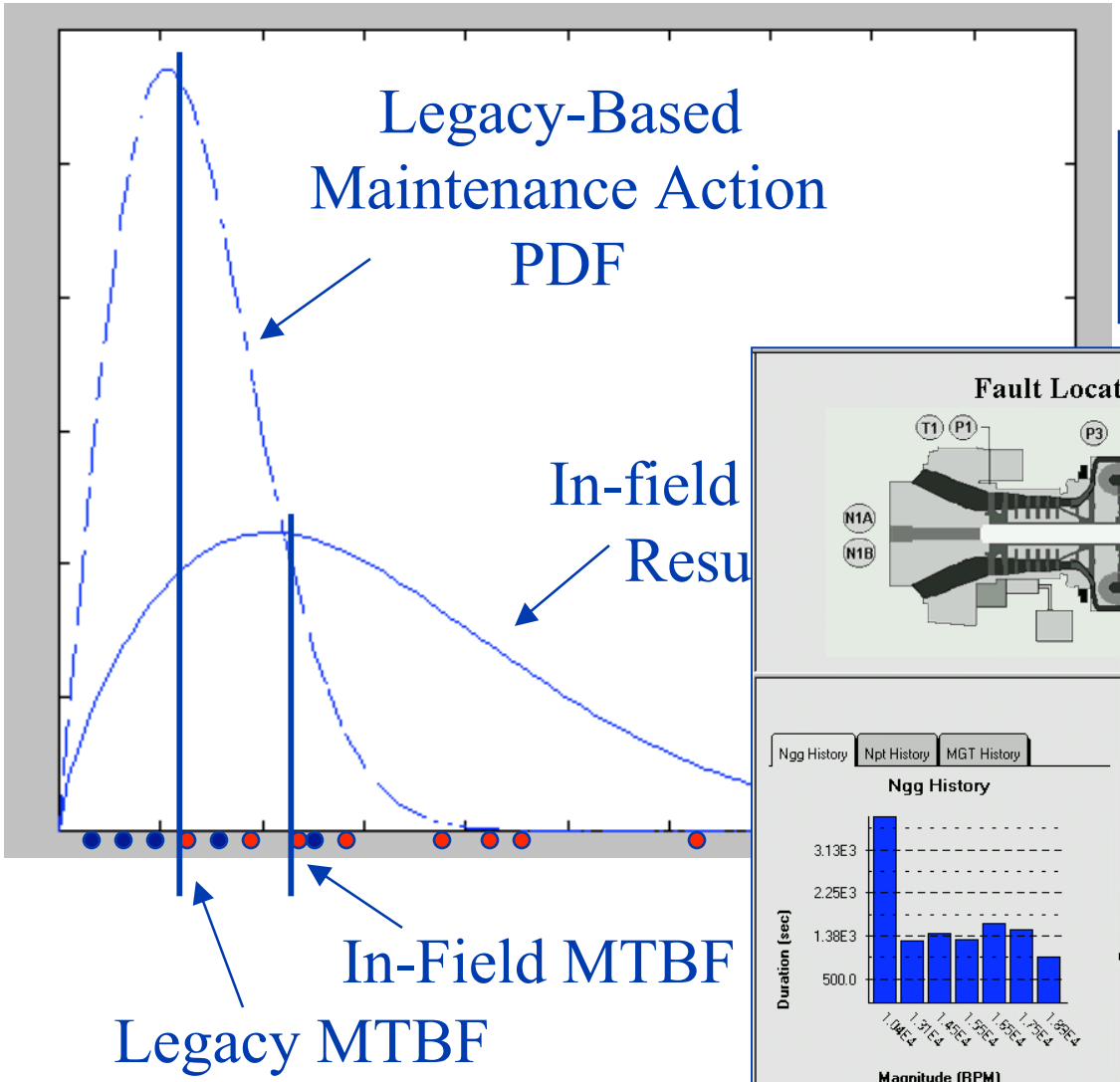
- Physics-based
- Real-time life prediction



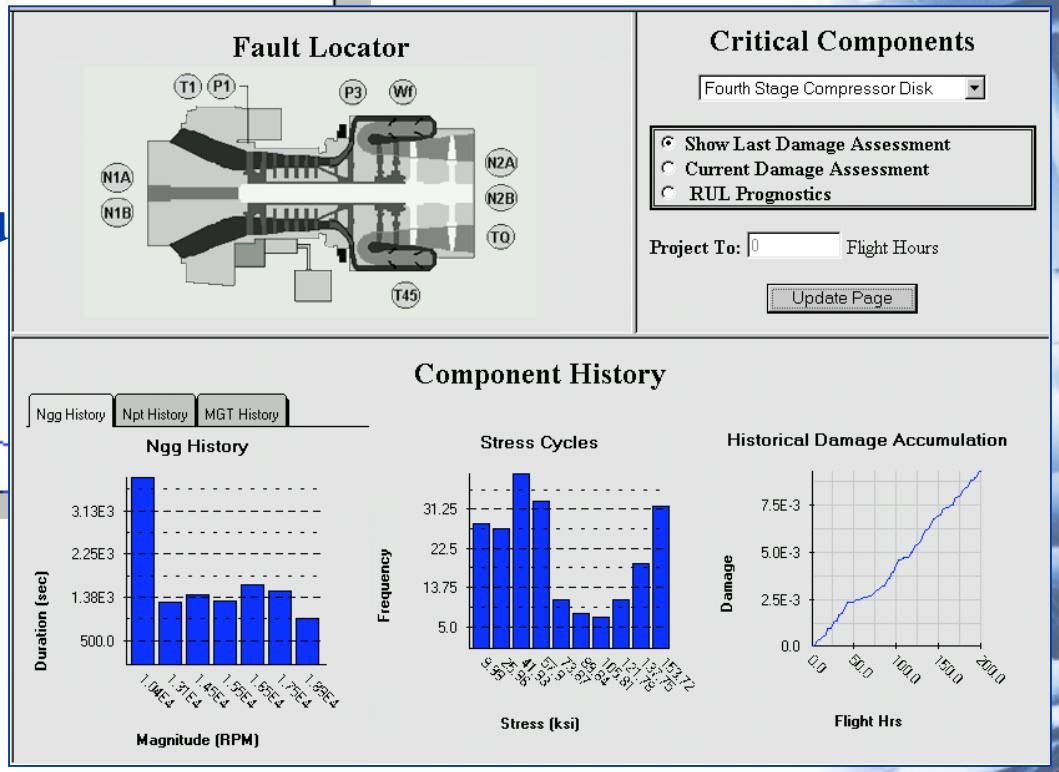
APU Performance Evaluation



Reliability and Usage Based Prognostics



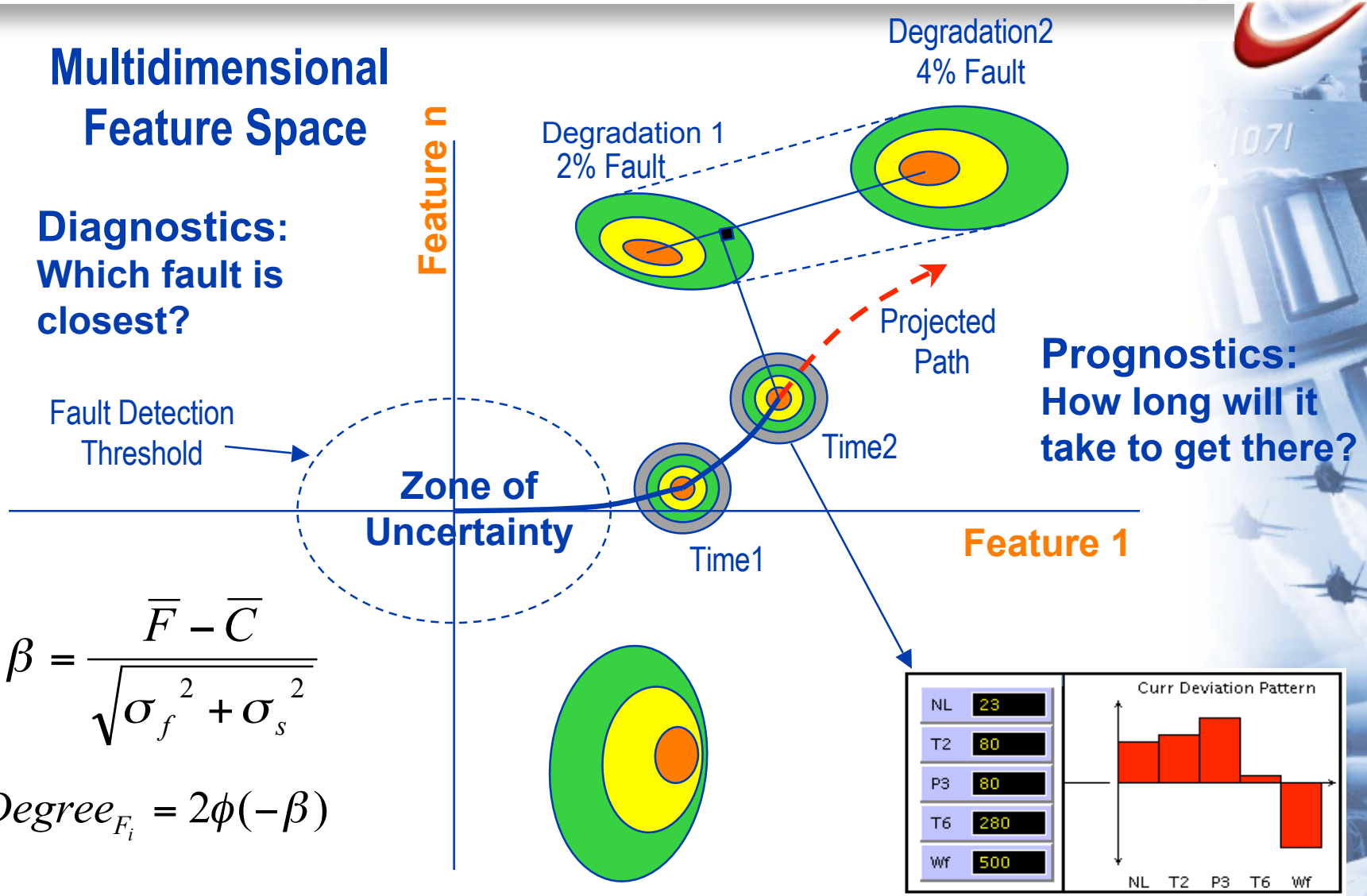
- **Weibull Formulation**
- **Update Capability**
  - New Data
  - Legacy Data



Evolutionary-based Prognostics

Multidimensional Feature Space

Diagnostics: Which fault is closest?

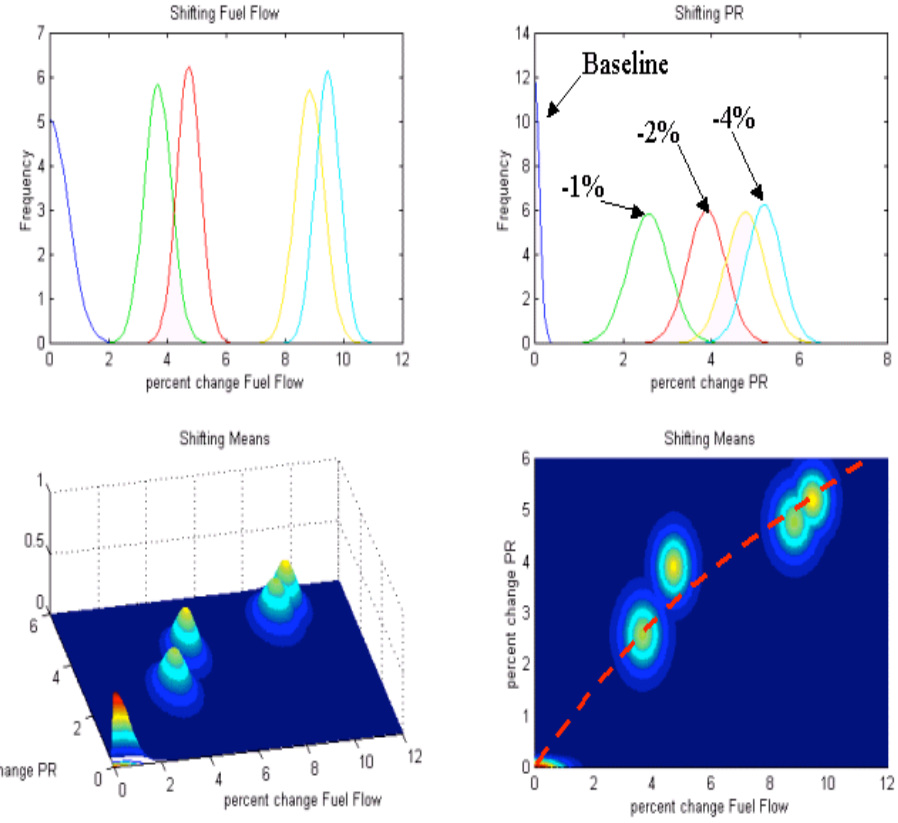


Prognostics: How long will it take to get there?

$$\beta = \frac{\overline{F} - \overline{C}}{\sqrt{\sigma_f^{\,2} + \sigma_s^{\,2}}}$$

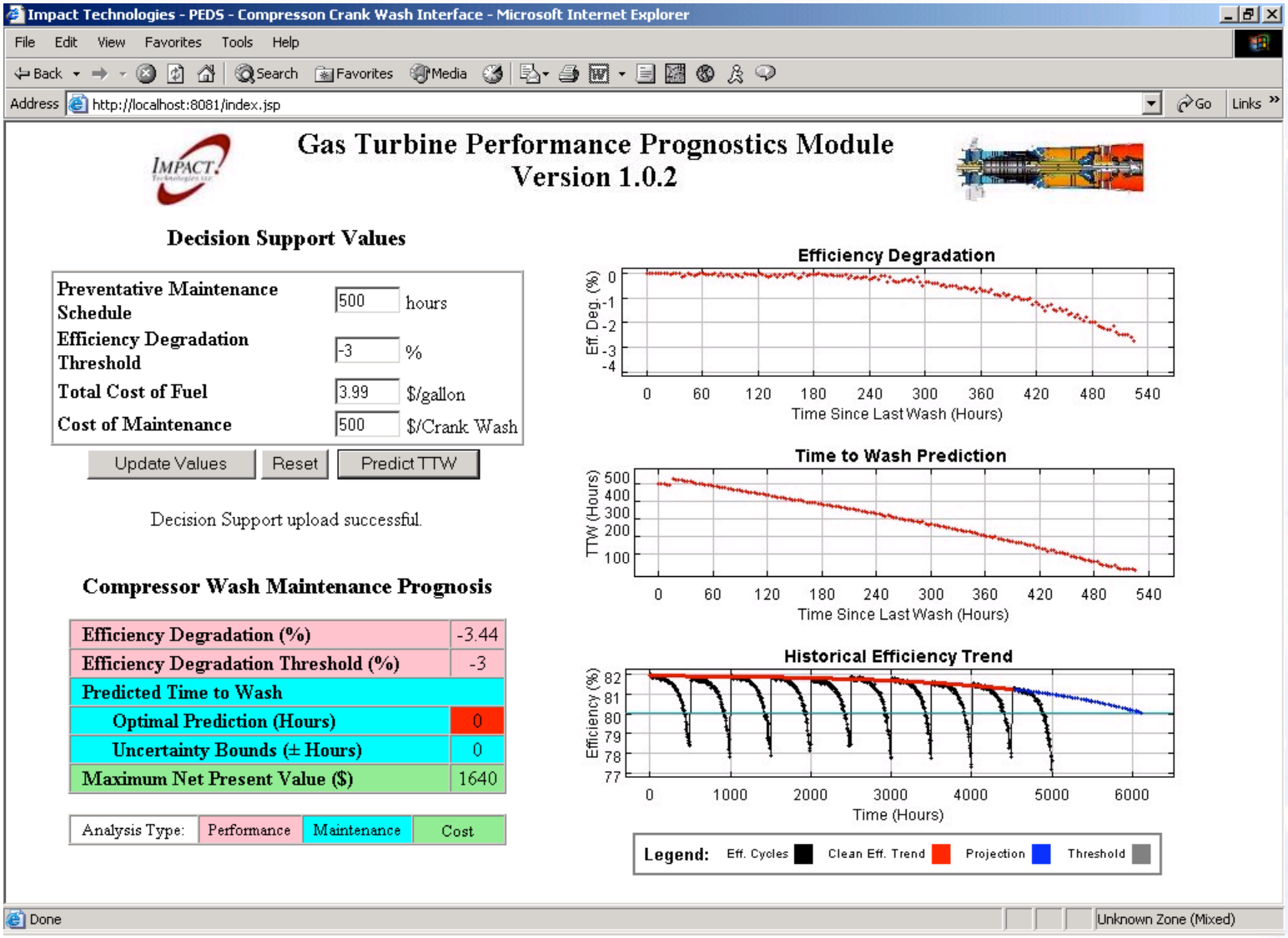
$$Degree_{F_i} = 2\phi(-\beta)$$

Compressor Wash Prediction Using Evolutionary Technique



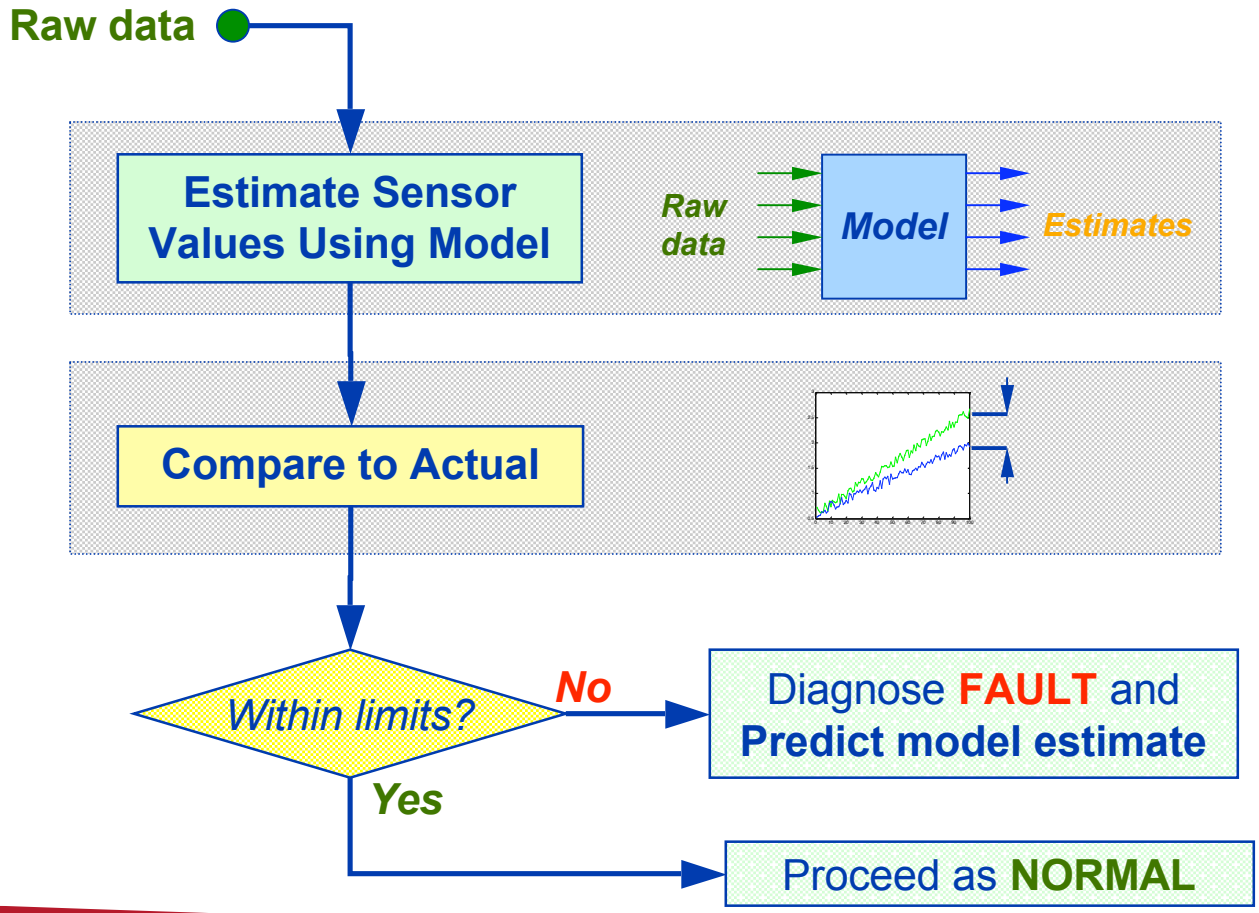
- Uses PR, Fuel Flow, and CDT to predict efficiency
  - CIP assumed
  - CDT measurement or pseudo-sensor needed
- Evolutionary classifier implemented for prediction

Gas Turbine Implementation

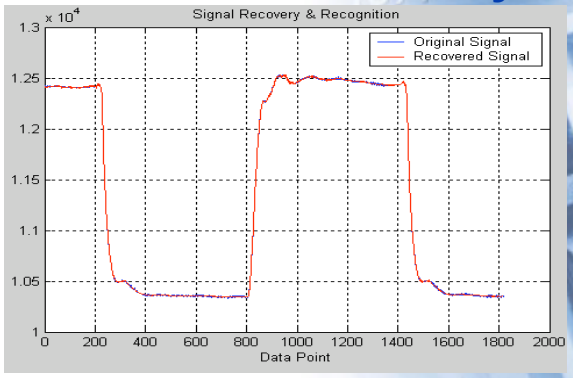


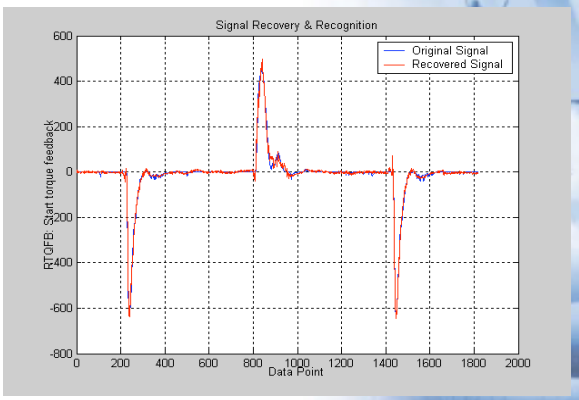
Data-Driven Prognostic Modeling

Creates an accurate data-driven model requiring no prior system knowledge, which can be used for fault detection and signal estimation

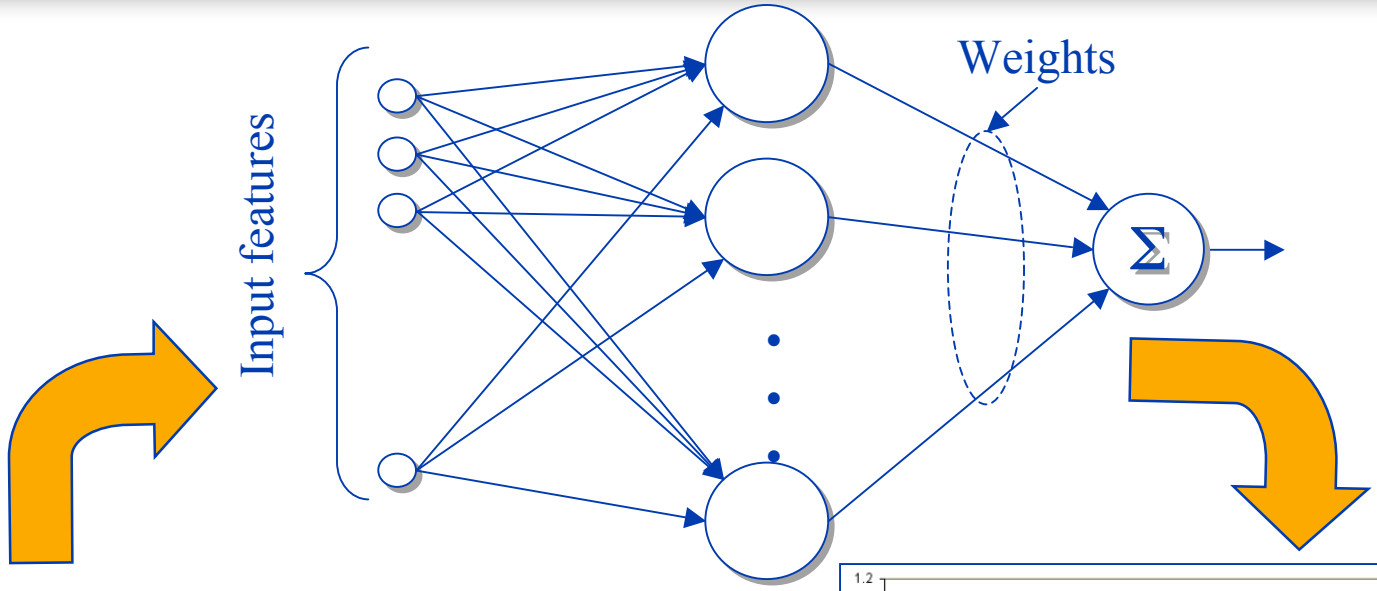


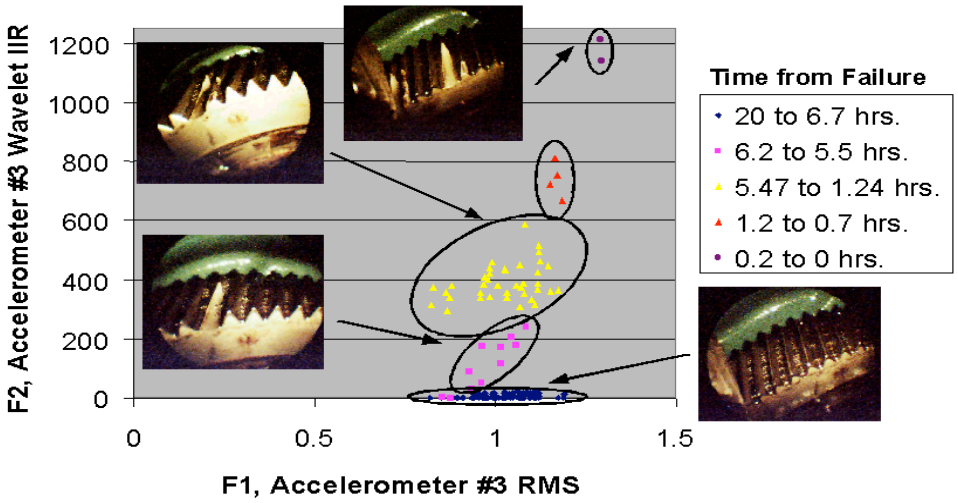
Prediction Accuracy

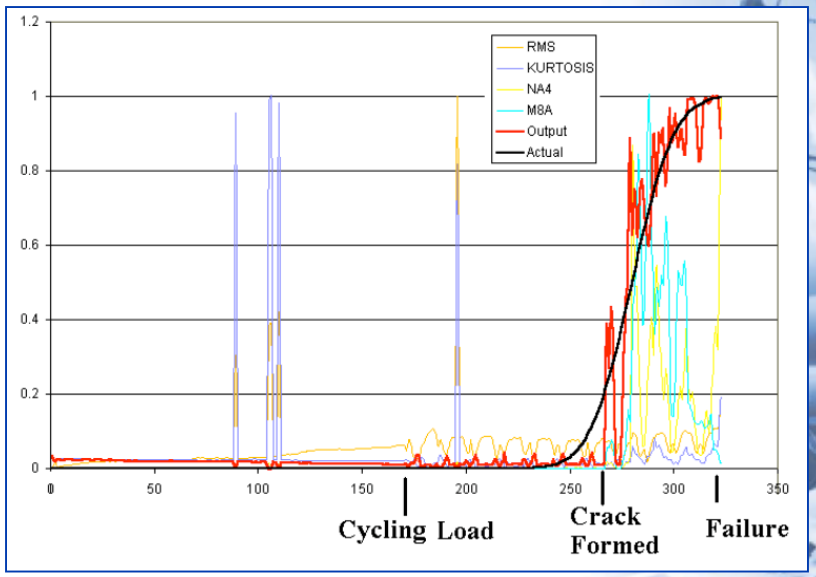




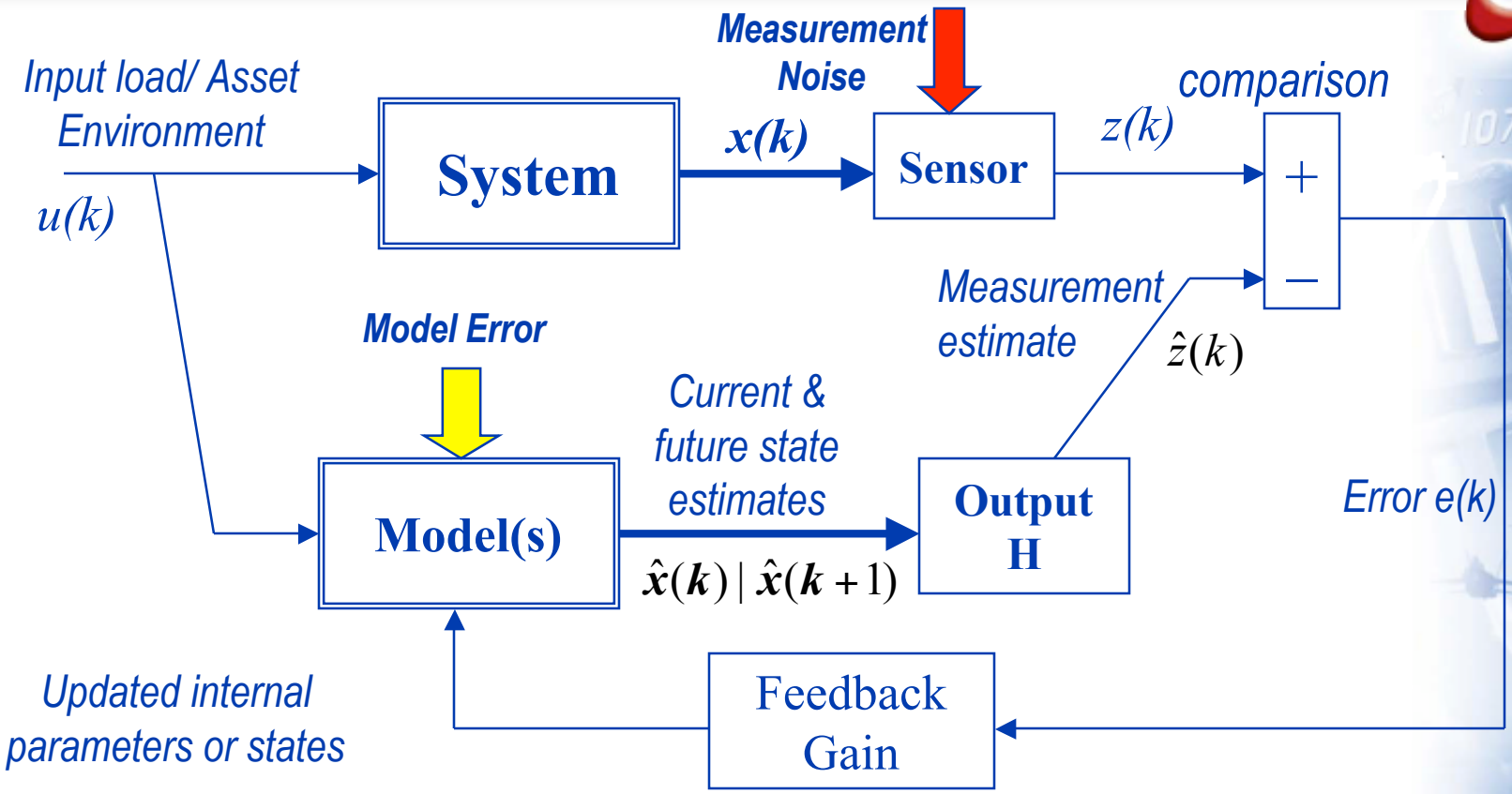
Neural Network/Data Driven Approaches







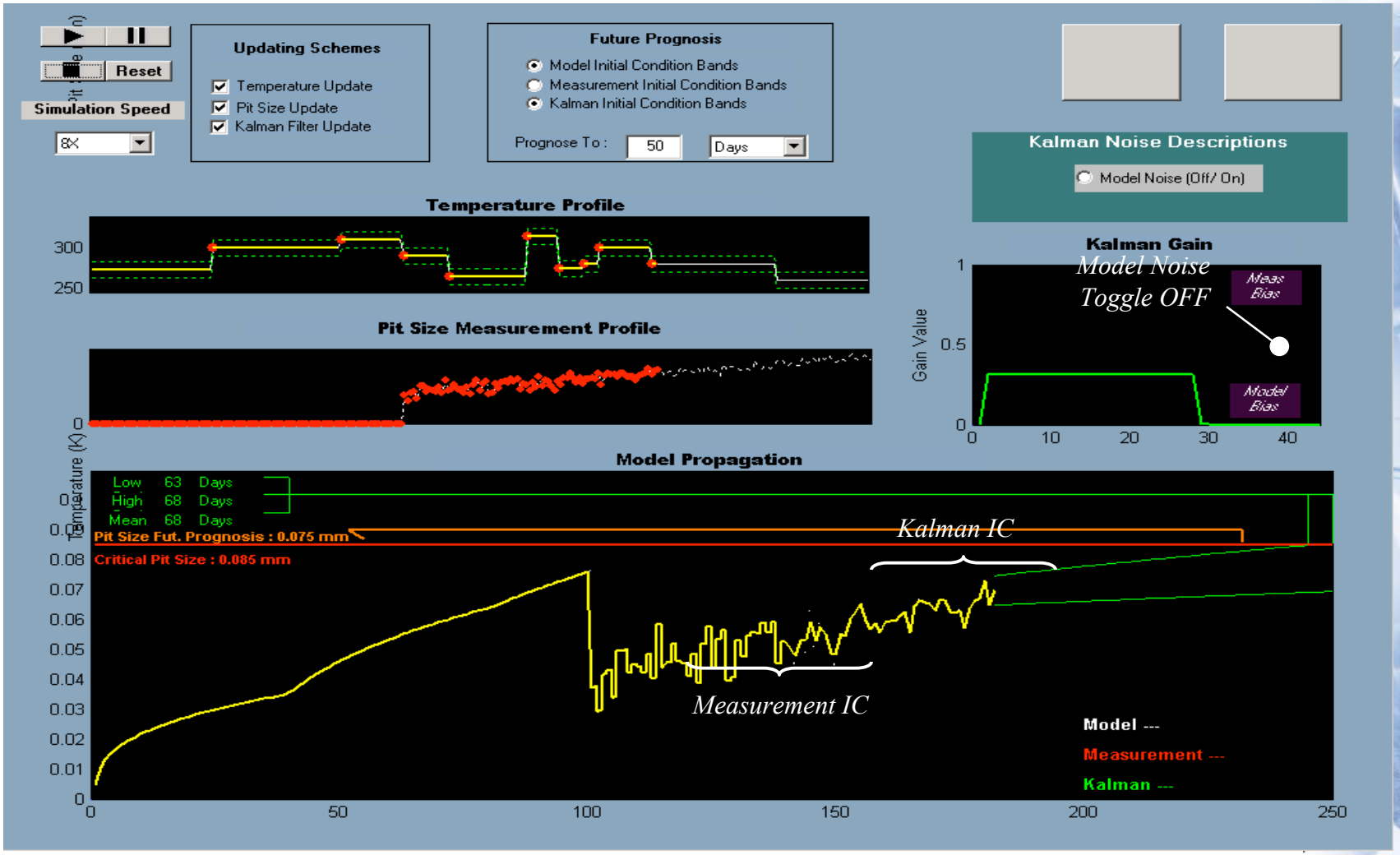
Parameter Estimation Based Approach



$$\hat{x}_{k+1} = \hat{x}_k + K_k(z_k - H_k\hat{x}_k) \quad | K_k = \text{Kalman Gain}$$

$$\hat{x}_{k+1} = (I - H_k K_k)\hat{x}_k + K_k z_k$$

Kalman Filter Example Results



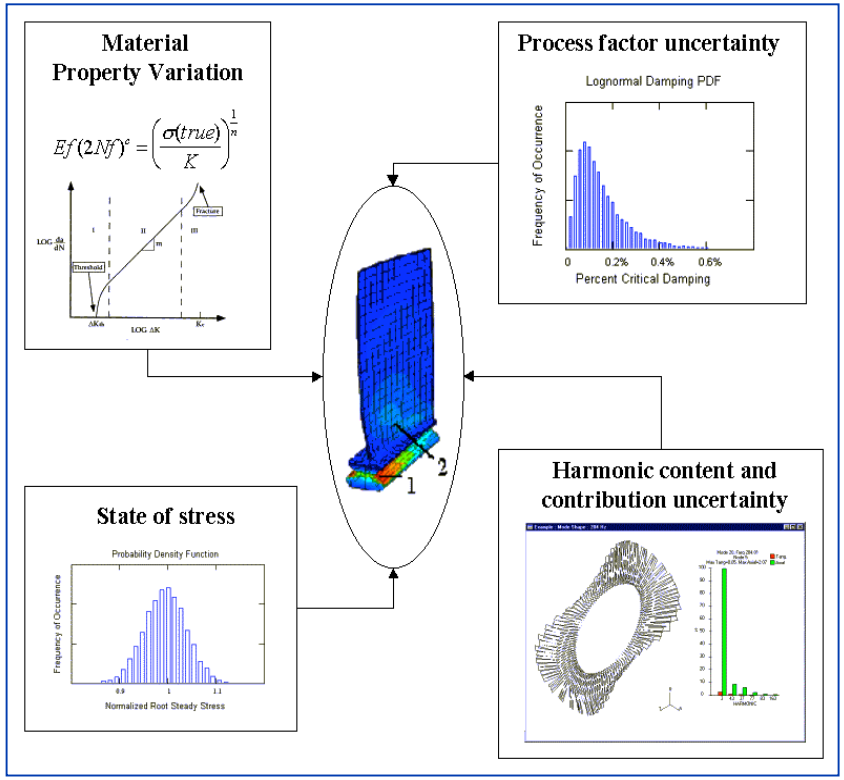
Model/Physics-Based Approaches

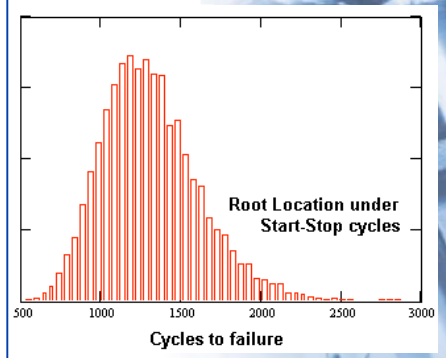
Diagnostic Results

Expected Future Conditions (based on historical conditions)

Experience - Based Information

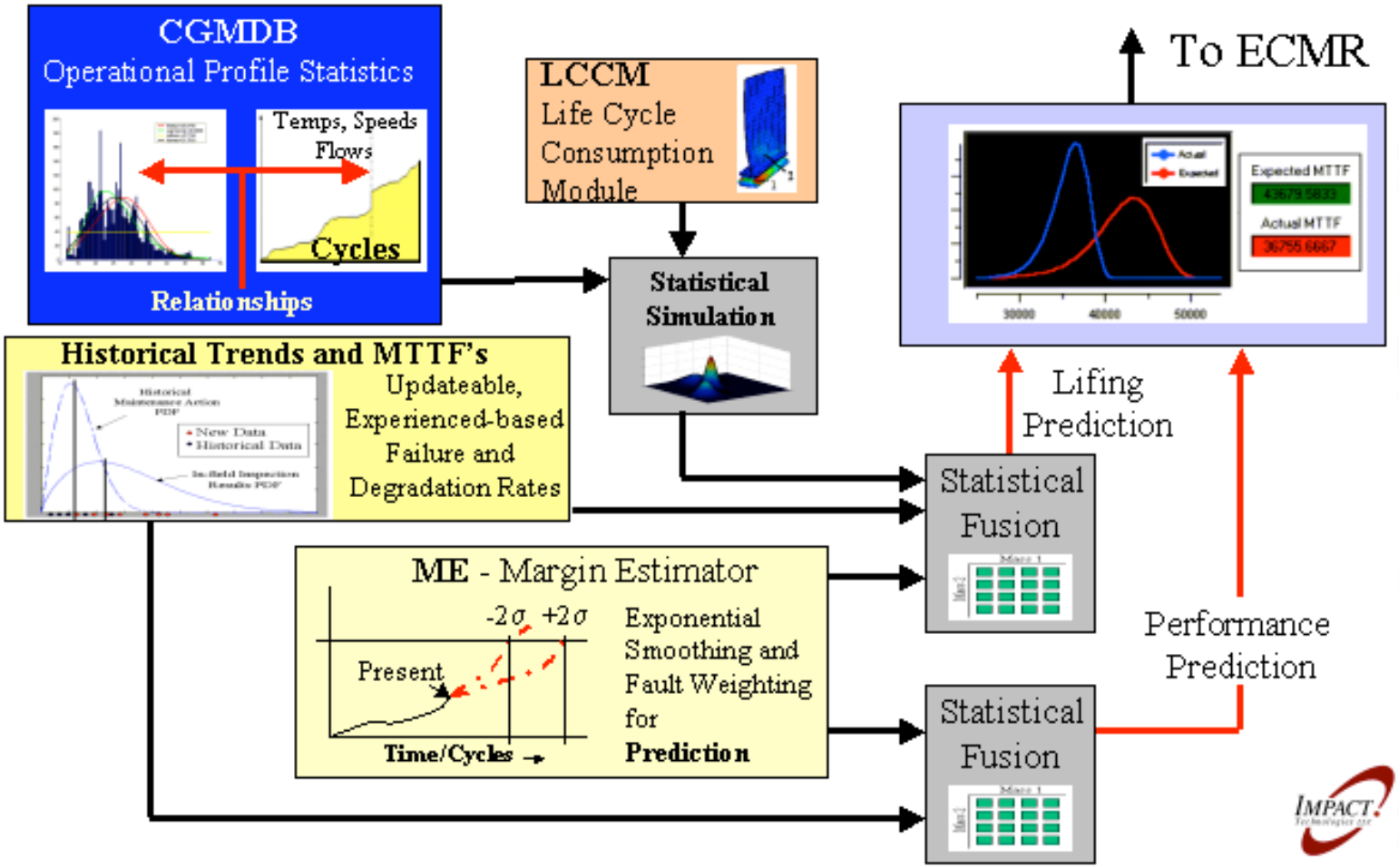
Physical Stochastic Model



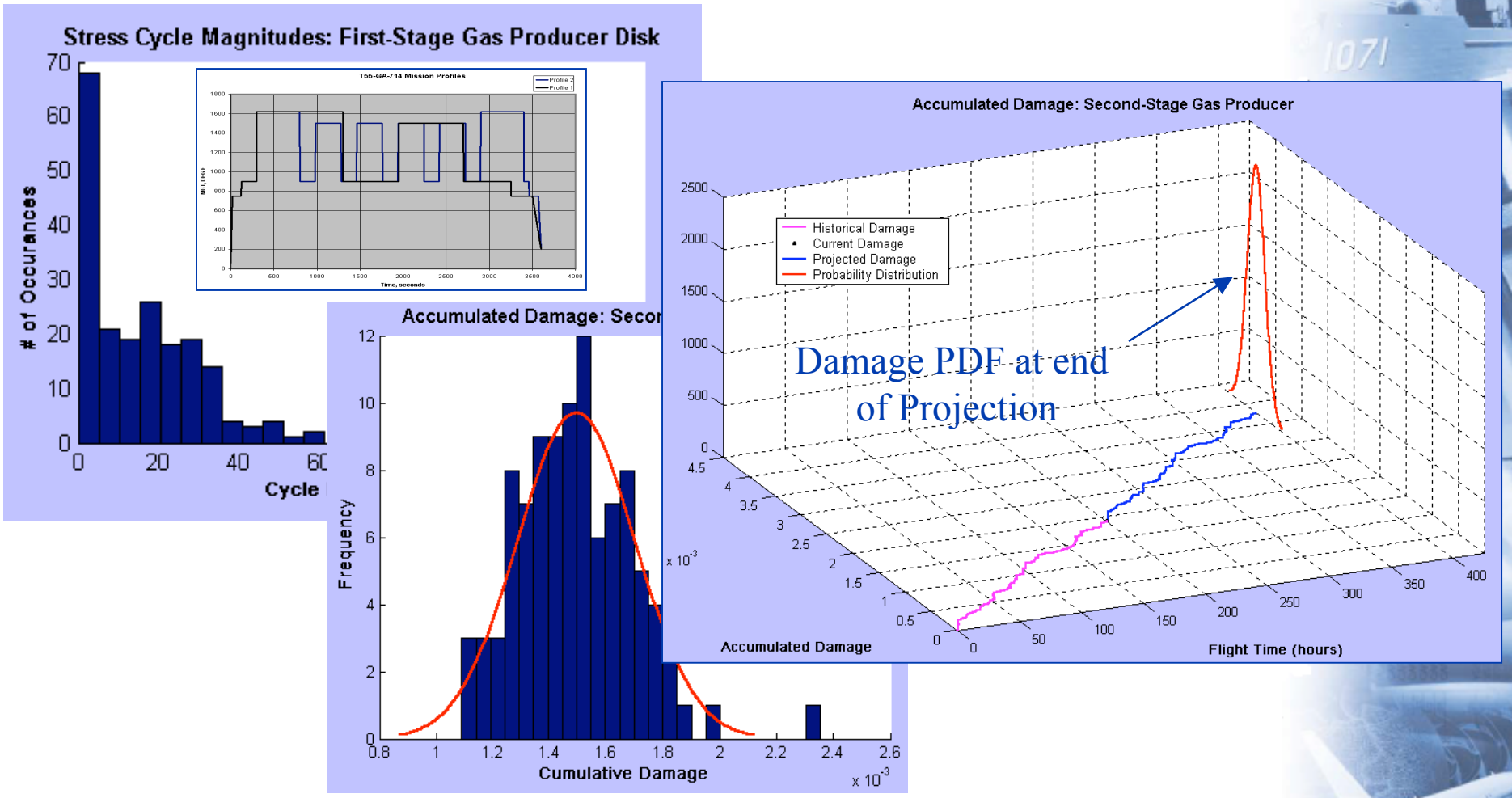


Current & Future Failure Prediction

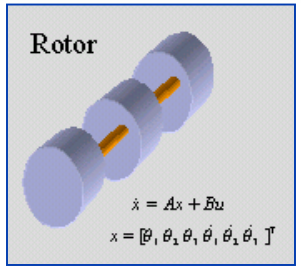
Model-Based Prognostic Example



Model-based Prognostic Results



Integrated Model/Data Driven Prognostic Approaches



System Level Model/Features

Raw Data

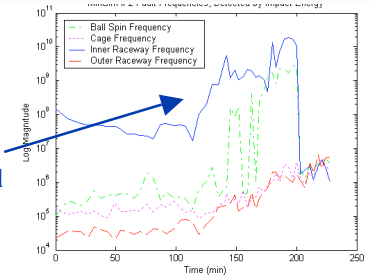
↓

Features

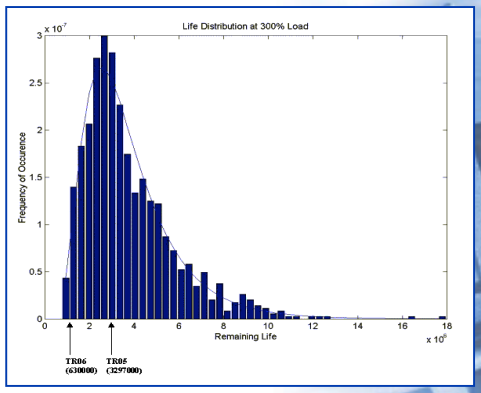
↓

State Awareness

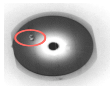
Spall Initiated

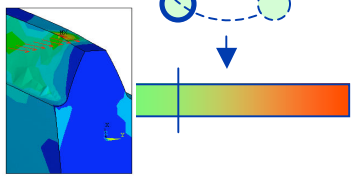


Component Level Features

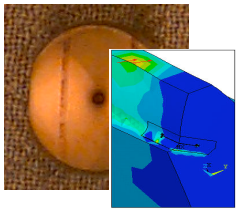


Initiation





Progression



Material/Physics Stochastic Models

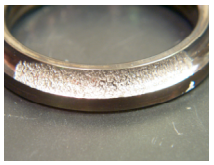
Probabilistic Fusion Process

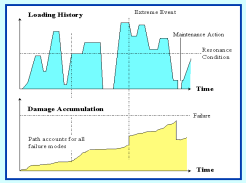
Current/Future Capability Prediction

Will it last the mission(s)?

What Operational changes must take place?

Reliability Information

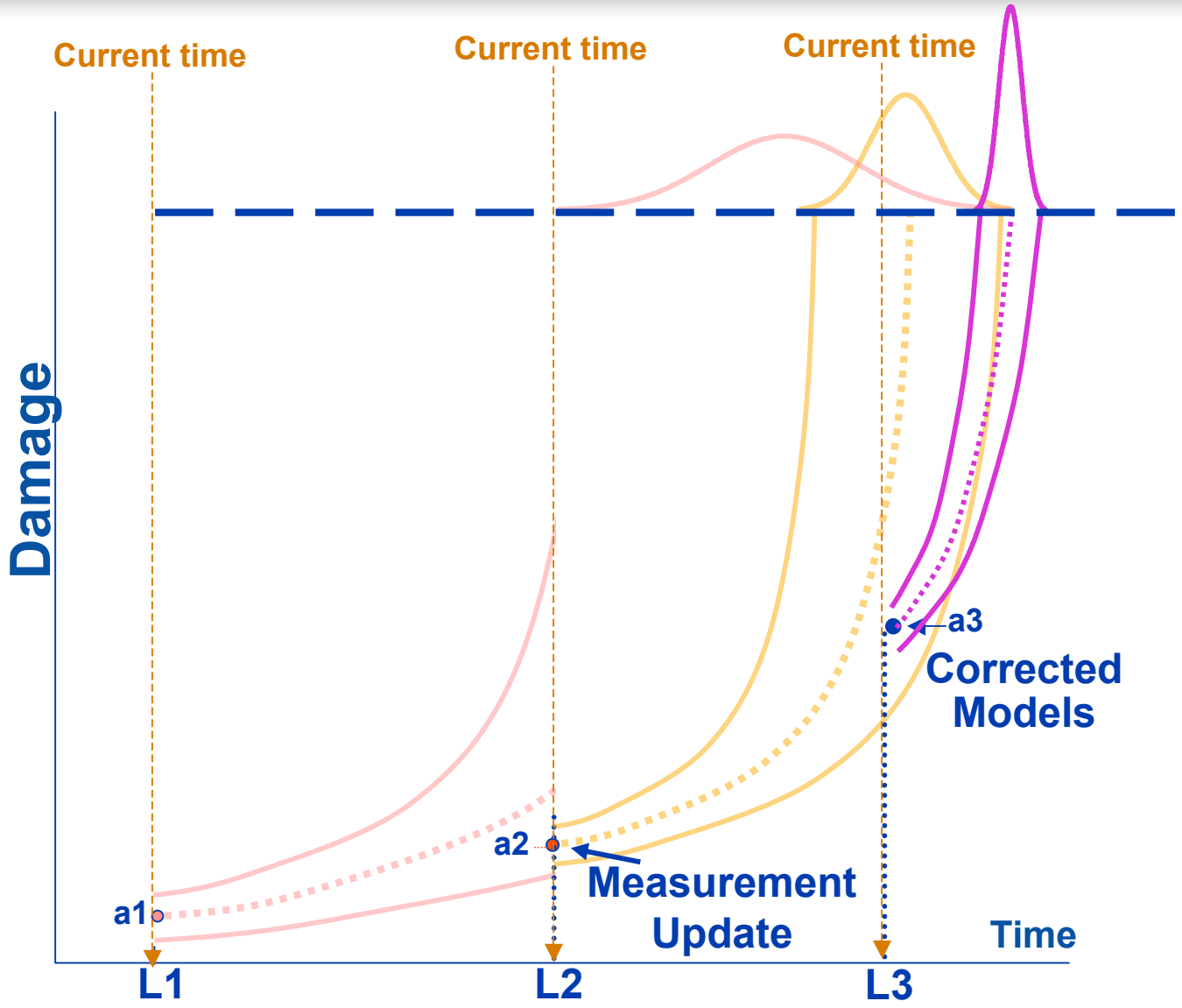




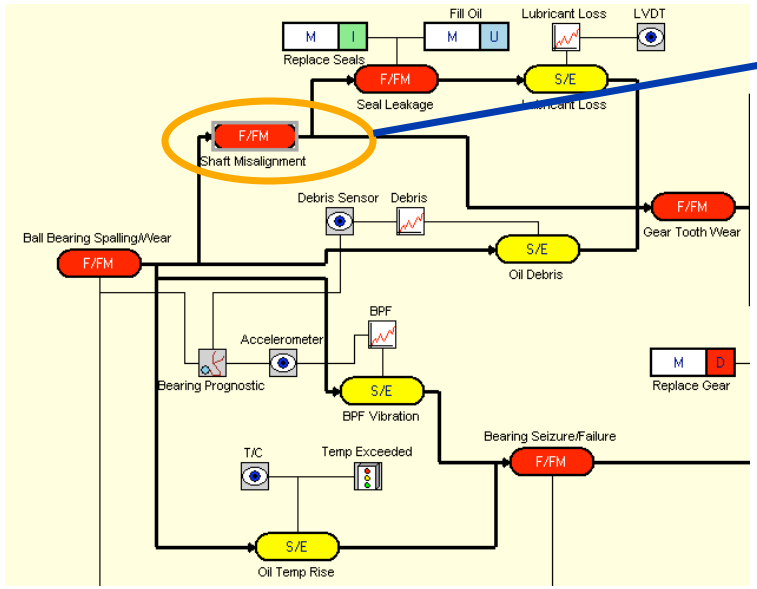
Expected Operating Conditions

Material Resume

Adaptation Iteratively Improves Prognosis

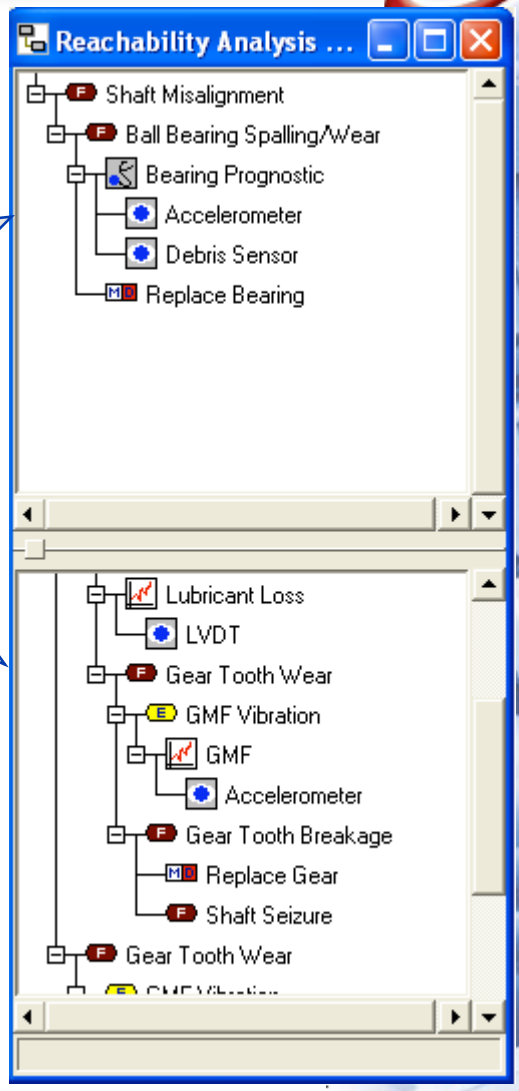


Integrated Model-Based Reasoning for Prognosis



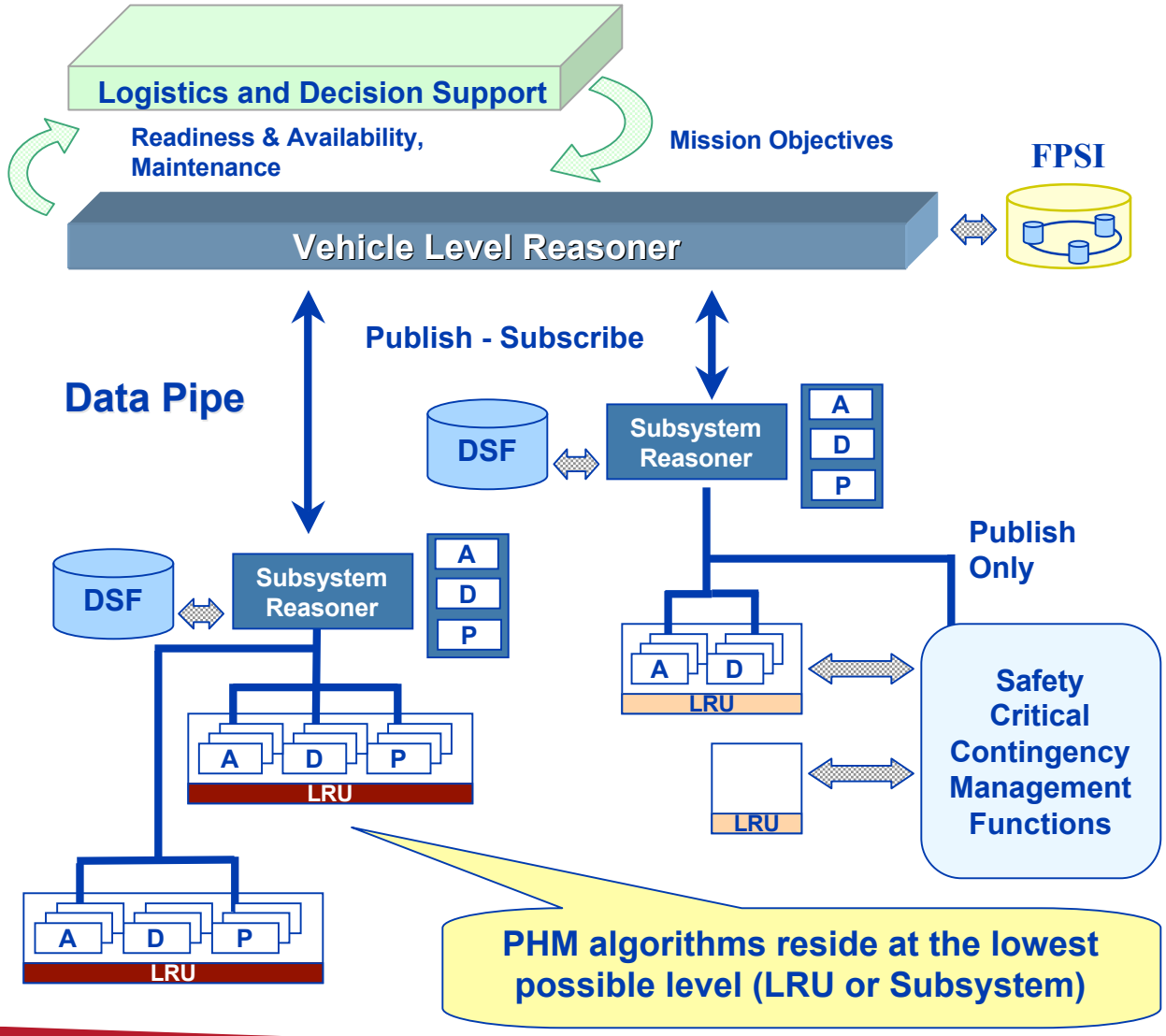
Upstream from F/FM or Sym/Eff

Downstream from F/FM or Sym/Eff



- Illustrates causal dependencies and fault paths across the entire system
- Reasoning algorithms traverse the topology

Prognostic Reasoning within a Distributed PHM Architecture



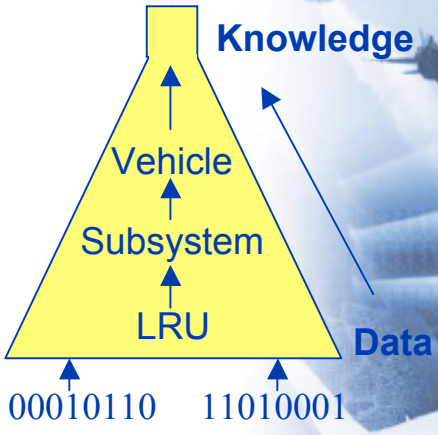
A/D/P
Anomaly Detection / Diagnostics / Prognostics Software

FPSI
Failure Propagation & Subsystem Interactions

DSF
Domain Specific FPSI

LRU
Line Replaceable Unit

Readiness, Availability, Maintenance



Prognosis Reasoning

Reasoning Algorithm

- Evidence-Based
- Temporal-Based

$$Rank_{FM(i)} = 1 + \frac{\sum_{j=1}^{PosE}(1 - FAR_j) - \sum_{k=1}^{NegE} RFP_k}{(PosE) + (NegE)}$$

"Acts On"

Integrated Model

Graphical XML Database

- PHM Technologies
- Mission Requirements
- Interconnected Sub Systems
- Symptoms/Effects
- Failure Propagation